Using Vision Modeling to Define Occupational Vision Standards

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ABSTRACT

A methodology is introduced to assist in the construction of performance-based occupational vision standards. A simple image discrimination model is first calibrated using stimuli representative of airframe and powerplant cracks. It is then used to predict simulated crack visibility for cracks of different lengths and widths. Visual acuity declines are simulated using a Gaussian blur function on the crack images. Crack width is shown to be a salient cue for crack detection. This modeling technique can generate the data necessary to construct empirically-based occupational vision standards. Future research will validate model predictions with human psychophysical data.

INTRODUCTION

Reviewing the occupational vision standards literature, Beard *et al.* (2002) found that the majority of standards are not empirically-based but rather appear to be arbitrary. A few standards have been empirically defined (Sheedy, 1980; Good & Augsberger, 1987; Padgett, 1989; Good, Weaver & Augsberger, 1996; Mertens & Milburn, 2000). Sheedy (1980), for example, measured the size and working distance of the critical visual details for police officers using a job-relevant task. Also using job-relevant tasks, Good *et al.* (1996) and Padgett (1989) used blurring lenses to simulate visual acuity declines for basket weavers and firefighters, respectively. Finally, Mertens and Milburn (2000) measured performance in color weak individuals on simulated ATC tasks to set an empirically defined color vision standard for air traffic controllers.

Currently no general standard exists in the aviation industry for the visual qualifications of aircraft maintenance inspectors. Some maintenance facilities use the visual acuity and color vision standards suggested in an FAA Advisory Circular AC No: 65-31, while other facilities have defined their own vision requirements. This illustrates the need for a uniform and universally accepted set of vision standards that would apply to all aircraft non-destructive inspection and testing (NDI/NDT) personnel. It is difficult, if not impossible, to eliminate human error in the process of inspection. Therefore interventions must be developed to reduce these errors and make the process more error-tolerant. Since visual inspection represents 80% of all aviation maintenance inspection tasks (Goranson & Rogers, 1983), one mitigation strategy is to define vision standards for this vision-intensive, safety-critical occupation.

In this paper we describe a model-based methodology for constructing an empirically-based visual acuity standard for a representative task performed by aircraft maintenance and inspection personnel. Computational models of human vision can make an important contribution toward defining occupational vision requirements. These models have been applied to measurements of image quality by comparing an original image and a reconstructed version of that image following image compression. The model predicts discriminability of the two images and thus the visibility of the compression artifacts (Watson, 1983; Ahumada, 1996). These discriminability models have also been successfully used to predict object detection in a complex background; such as the detectability of camouflaged military tanks in naturalistic scenes (Rohaly *et al.*, 1997), simulated cancerous tumors (Eckstein *et al.*, 1997) and simulated aircraft on a runway (Ahumada & Beard, 1997).

To obtain a visual acuity standard estimate using image discrimination models, we follow a multi-step process. First, the model is calibrated using laboratory stimuli that are representative of blurred and unblurred airframe and powerplant cracks. These representative stimuli were a subset of the standard Modelfest images (Watson, 2000), whose contrast thresholds have been measured in numerous laboratories and will be used to define normal observer model parameters. Second, the calibrated model was used to predict simulated crack visibility for cracks of different lengths and widths as a function of blur. Unlike earlier studies, reduced visual acuity is simulated within the image, rather than with blurring lenses, so that the image characteristics are exactly known. This step provides an estimate of contrast sensitivity reduction as a function of blur, so that if the tolerable loss in contrast sensitivity can be specified, the corresponding visual acuity is then specified. In future studies, human psychophysical measurements will validate the simulated crack predictions. In addition, the model will be used to compare the simulated crack predictions to predictions for actual crack images in a natural aircraft scene. And finally, we will validate the natural scene predictions with human-in-the-loop data. In this paper the results for the first two steps of this process are presented.

The purpose of this paper is threefold. (1) to introduce a new methodology for determining occupational vision requirements, (2) to present the technique used for model calibration, and (3) to determine model predictions for simulated crack images over a range of widths and lengths at different levels of visual acuity.

METHODS & RESULTS

Representative Defects

Aircraft inspection is a complex process, requiring many tasks, skills, and procedures. One purpose of inspection is to detect surface discontinuities such as cracks within the airframe and powerplant regions of the aircraft. Cracks are typically caused by two surfaces being overlaid at a boundary (Hellier, 2001). Since these cracks may be very small and of low contrast, adequate visual acuity is likely to be involved in their detection. After consultation with domain experts, crack detection was chosen as the representative task to model in order to ultimately set a visual acuity standard. Visual acuity refers to a measure of spatial resolution for a high contrast, static image.

Two steps were taken before obtaining model predictions for crack detection as a function of blur. The upper left image shown in Figure 1 was the original defect image of an airframe. A crack runs horizontally across the image. Using a drawing tool, the crack was deleted from the image while maintaining the integrity of the background image (shown on the upper right). Both images were then blurred as shown in the lower two panels of Figure 1.

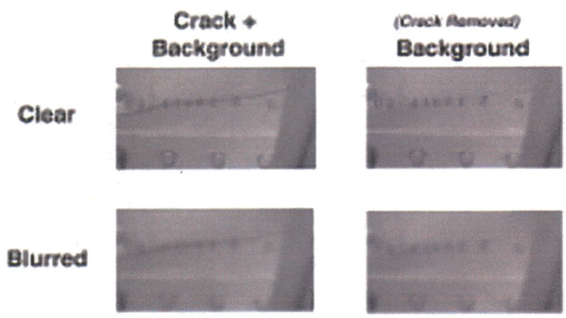

Figure 1. (Upper left) Original image of a crack defect on an airframe surface. (Upper right) The crack has been removed using a common drawing tool. (Lower left) The original image has been blurred to simulate 20/200 visual acuity. (Lower right) The "crack removed" image has been blurred to simulate 20/200 visual acuity.

A Simple Model

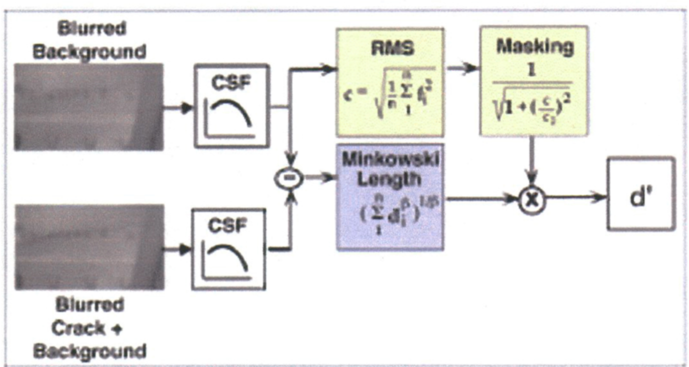

Figure 2. Schematic of an image discrimination model. The upper image on the left is the blurred background image with the crack removed and the lower image is the blurred background-plus-defect image. The two images (contrast images) enter the visual system, where they are filtered by a difference-of-Gaussian blurring function (Contrast Sensitivity Function, CSF). The difference of the filtered images is the visible defect contrast image and the beta-norm of its contrast is the Minkowski length. The background image is assumed to be the masker and its standard deviation , c, reduces the defect image contrast by means of a gain-control factor. The product of these factors represents the predicted sensitivity or the number of just noticeable differences (JNDs) of the crack defect.

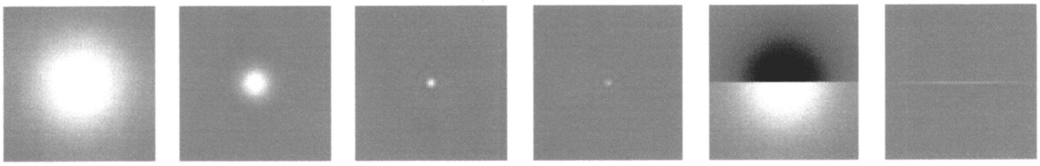

Figure 3. Stimuli used to calibrate the contrast discrimination model. The four leftmost images are Gaussian blobs with decreasing standard deviations. The fifth image is an edge and the sixth image is a line.

Image discrimination models predict the visibility difference between two similar images. The models take two images as input, and output a prediction of the number of Just Noticeable Differences (JNDs) or the smallest detectable difference between the two images. In this version of the model, one luminance image is considered to be a blurred version of the background image and the other is the blurred background-with-crack image. These images are filtered using the Contrast Sensitivity Function (CSF) in order to normalize sensitivity to different spatial frequencies. The CSF is a graph depicting a person's ability to detect a stimulus as a function of stimulus spatial frequency. The model takes the contrast energy in the target and adjusts it by the background standard deviation. For a more detailed description of the model see Rohaly *et al.* (1997).

Model Calibration

To provide a common data set for the contrast detection model development, the Modelfest project developed a set of 44 images, most of which are various sinusoidal grating patches (the entire set of 44 calibration images can be obtained from *http://vision.arc.nasa.gov/modelfest*). These images have been successfully used to test and calibrate detection models. To calibrate our model, six of the 44 images were chosen because of their physical similarity to aircraft crack defects and their blurred versions. These six images are shown in Figure 3.

Earlier predictions of real world stimuli (Rohaly *et al.*, 1997; Ahumada & Beard, 1997) have assumed a CSF with a sinusoidal grating threshold of 1%. To fit the average Modelfest thresholds (n=16) for the stimuli in Figure 3 a best grating threshold of 0.7% was found. The best fit Minkowski summation exponent was 2.53 (slightly higher than the Euclidean distance exponent of 2). These values are less than that found for the entire set (Watson. 2000), probably because many other images in the full set contain extended, high spatial frequency features, whereas the six images used here either were localized within a small spatial area or contained only extended low frequency energy. The RMS error for the model, adjusting the peak contrast sensitivity and the summation exponent, but not the shape of the CSF function was a very good 1.4 dB.

Simulating Visual Acuity Decline

Although the shape of the human blur function differs between individuals and changes for different optical conditions, it can be approximated by a Gaussian spread function. The model has a difference-of-Gaussians contrast sensitivity function with a center Gaussian spread of 2 min. To simulate different levels of visual acuity, the image is blurred with a Gaussian and acuity is reported as the ratio of the effective center spread to the original model value. Thus we are assuming that the model has 20/20 vision. For example, if the blur has a spread of 2 min, the effective center Gaussian spread will be root 2 times 2 min (Pythagorean rule) so that the effective acuity will be 20/28.

Model Predictions

The visibility of a set of simulated cracks was predicted as a function of blur (simulating visual acuity declines) for a range of lengths and widths. The widths were 0.5, 1, 2, 4, and 8 min. The lengths were the widths times 1, 2, 4, 8, and 16. Figure 4 shows how the threshold contrast for four of these images was elevated as a function of blur relative to the threshold for the unblurred image. The top curve is the result for the pinpoint crack (e.g., 0.5 min x 0.5 min). The threshold for this image is more affected by blur than the threshold for any other image. The figure shows that if the allowed sensitivity degradation were 6 dB (a factor of 2 in contrast), the allowable acuity degradation would be about 20/50.

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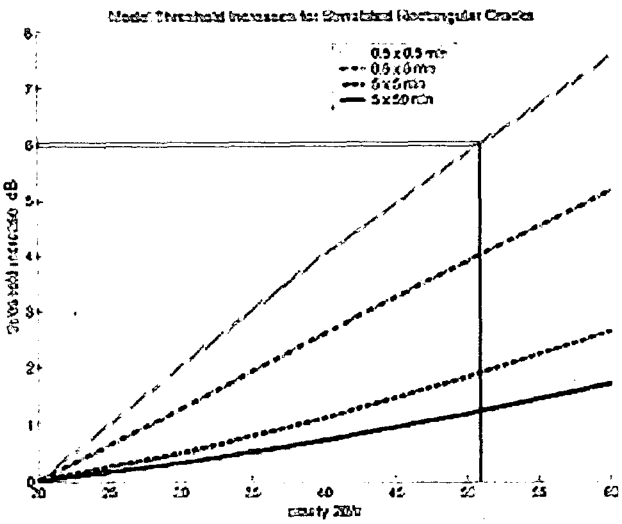

Figure 4. Blur-generated contrast threshold increments in decibels of contrast as a function of visual acuity decline for four of the crack length and widths described in the text. The top curve represents the smallest crack (0.5 min by 0.5 min), the bottom curve is for the biggest crack (8 min by 128 min).

DISCUSSION

The first aim of this paper was to describe a methodology that may be used to generate empirically-based occupational vision standards. This methodology does not provide a standard, but it converts the problem to specifying a desired physical limitation in performance. The most important feature of the method is that it allows a large number of critical stimuli to be specified without requiring that a large number of stimuli actually be tested using human observers. In this case, the stimulus most sensitive to the manipulation being considered (a small crack) and the manipulated versions themselves (Gaussian blobs) happened to be in a set of well-studied stimuli. However, if it was decided that only stimuli with particular characteristics (e.g., cracks of a certain length) were important for setting the standard, the results might then need to be confirmed by psychophysical human-in-the-loop experiments. The model has shown to do well on uniform backgrounds, but needs testing in complex, blurred backgrounds.

Here this technique is used to help define the spatial vision requirements for aircraft NDI/NDT personnel using simulated crack images. These modeling results will also help define the range of parameters that need to be tested in the human psychophysical experiments.

Vision is a fundamental component of effective aircraft inspection. All the same, so too are other cognitive factors such as attention. memory, and experience. Inspectors are knowledgeable about individual components as well as the overall aircraft being inspected, thus they possess the background to properly locate, identify, and evaluate aircraft defects. Therefore, although vision is a critical component in inspection, other factors weigh in heavily on the naturalistic task.

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